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The Application of Zhang-Gradient Method for Iterative Learning Control

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Abstract. The novel sufficient conditions for nonlinear systems without and with time-delay, whose initial state are zero or not, are studied using the λ-norm, Zhang-gradient method and retarded Gronwall-like inequality. An examples is shown the effectiveness of the mentioned technique.

Keywords: Iterative learning control, Zhang-gradient method, tracking error; convergence, time delay

1 Introduction

Iterative learning control methodology, which is proposed by Arimoto et al. in 1984 (See[1]), is to utilize the previous control information of the studied systems. The repetitive behavior has been a major research area and a hot issue in recent years (See[2-15]).

Recently, Zhang-gradient method has shown their powerful performance in solving online time-varying control problem (See[16-20]). The Zhang-gradient method is based on an indefinite error-monitoring function (See[20]), but the gradient dynamics method is usually designed from a norm or square-based energy function.

Stabilization problem of control systems has received some research results and have been reported in the literature[3,11,13,15,21-29]. However, only a few results combining with the iterative learning control items and Zhang-gradient method are available for nonlinear systems. In this paper, under the case that the initial state $y_k(0)=y_{k+1}(0)$ or $y_k(0)\neq y_{k+1}(0)$, the iterative learning controller of nonlinear systems is designed by using Zhang-gradient method and λ-norm.

2 Preliminaries

Throughout this paper, $\|x\|=\left(\sum_{i=1}^{n}x_i^2\right)^{1/2}$ is said to be the 2-norm for the vector $x=(x_1,x_2,\ldots,x_n)^T$, while the λ-norm for the $x(t)$ function is defined as $\|x(t)\|_\lambda=\sup_{t\in[0,T]}\left\{e^{-\lambda t}\|x(t)\|\right\}$, where $\lambda>0$.

Lemma. [10,30] Consider $\sup_{t\in[0,T]}\left\{e^{-\lambda t}\int_0^t\|x(t)\|d\tau\right\}\le\frac{1}{\lambda}\|x(t)\|_\lambda$.

3 Design of Iterative Learning Controller of Nonlinear Systems

In this section, we will take account of two cases about the iterative initial state vector $y_{k+1}(0)=y_k(0)$ and $y_{k+1}(0)\neq y_k(0)$, respectively, of nonlinear systems without and with time delay.

Theorem 1. Consider iterative learning control on the system

$$\dot{y}_k(t)=f\left(t,y_k(t)\right)+u_k(t) \tag{2}$$

where $y_k(t)\in R^n$ is the kth iterative state vector, $f(t,y_k(t))$ is the nonlinear operator $[0,T]\times R^n\to R^n$, and satisfies

$$||f(t,y_{k+1}(t))-f(t,y_k(t))||\le l_f||y_{k+1}(t)-y_k(t)|| \tag{3}$$

$u_k(t)$ is the k-th iterative control input, T is a constant.

When $y_{k+1}(0)=y_k(0)$, the iterative learning controller is designed as

$$u_{k+1}(t) = u_k(t) + m\hbar\left(e_k(t)\right) \tag{4}$$

When $y_{k+1}(0)\neq y_k(0)$, the iterative learning controller is designed as

$$u_{k+1}(t) = u_k(t) + m\hbar\left(e_k(t)\right) + \psi_{k,h}(t)\left(y_{k+1}(0) - y_k(0)\right) \tag{5}$$

where $e_k(t)=y_d(t)-y_k(t)$ is Zhang function (i.e., error function), $y_d(t)$ is a desired output, $\hbar\left(e_k(t)\right)$ is a monotonically increasing odd function, $m<0$ is a constant, and $\int_0^t \psi_{k,h}(s)\,ds = 1$.

Besides, according to Zhang-gradient method (See [31,32]), the formula can be used

$$\dot{e}_k(t) = -\mu\hbar\left(e_k(t)\right), \quad \mu>0 \tag{6}$$

If there exist a constant $\lambda>0$ such that

$$\left(\frac{|\mu+m|}{\mu} + \frac{l_f}{\mu}\cdot\frac{|m|}{\lambda - l_f}\right) < 1 \tag{7}$$

then the system (2) can guarantee that $||y_d(t)-y_k(t)||$ is bounded and $y_k(t)$ can track $y_d(t)$ on $t\in[0,T]$, i.e. $\lim_{k\to+\infty} y_k(t) = y_d(t)$.

Proof. From $e_k(t)=y_d(t)-y_k(t)$, we know that $e_{k+1}(t)=e_k(t)+y_k(t)-y_{k+1}(t)$. So

$$\dot{e}_{k+1}(t) = \dot{e}_k(t) + \dot{y}_k(t) - \dot{y}_{k+1}(t)$$

According to (2), (3) and (6), we have

$$\begin{aligned}
-\mu\hbar\left(e_{k+1}(t)\right) &= -\mu\hbar\left(e_k(t)\right) + f\left(t,y_k(t)\right) + u_k(t) - f\left(t,y_{k+1}(t)\right) - u_{k+1}(t) \\
&= -\mu\hbar\left(e_k(t)\right) - m\hbar\left(e_k(t)\right) + \left[f\left(t,y_k(t)\right) - f\left(t,y_{k+1}(t)\right)\right] \\
&= -\left(\mu+m\right)\hbar\left(e_k(t)\right) + \left[f\left(t,y_k(t)\right) - f\left(t,y_{k+1}(t)\right)\right]
\end{aligned}$$

$$\hbar\left(e_{k+1}(t)\right) = \frac{\left(\mu+m\right)}{\mu}\hbar\left(e_k(t)\right) + \frac{1}{\mu}\left[f\left(t,y_{k+1}(t)\right) - f\left(t,y_k(t)\right)\right]$$

$$\left\|\hbar\left(e_{k+1}(t)\right)\right\| \leq \frac{|\mu+m|}{\mu}\left\|\hbar\left(e_k(t)\right)\right\| + \frac{l_f}{\mu}\left\|y_{k+1}(t) - y_k(t)\right\|$$

Taking λ-norm, we have

$$\left\|\hbar\left(e_{k+1}(t)\right)\right\|_\lambda \leq \frac{|\mu+m|}{\mu}\left\|\hbar\left(e_k(t)\right)\right\|_\lambda + \frac{l_f}{\mu}\left\|y_{k+1}(t) - y_k(t)\right\|_\lambda \tag{8}$$

From iterative law (4), (5) and Lemma,

$$\begin{aligned}
y_{k+1}(t) - y_k(t) &= \int_0^t \left(\dot{y}_{k+1}(\tau) - \dot{y}_k(\tau)\right)d\tau + \left(y_k(0) - y_{k+1}(0)\right) \\
&= \int_0^t \left(f\left(t,y_{k+1}(t)\right) - f\left(t,y_k(t)\right)\right)dt + \int_0^t \left(u_{k+1}(t) - u_k(t)\right)dt + \left(y_k(0) - y_{k+1}(0)\right) \\
&= \int_0^t \left(f\left(t,y_{k+1}(\tau)\right) - f\left(t,y_k(\tau)\right)\right)d\tau + \int_0^t m\hbar\left(e_k(\tau)\right)d\tau
\end{aligned}$$

$$\left\|y_{k+1}(t) - y_k(t)\right\| \leq \int_0^t l_f\left\|y_{k+1}(\tau) - y_k(\tau)\right\|d\tau + \int_0^t |m|\left\|\hbar\left(e_k(\tau)\right)\right\|d\tau$$

$$\left\|y_{k+1}(t) - y_k(t)\right\|_\lambda \leq \frac{l_f}{\lambda}\left\|y_{k+1}(t) - y_k(t)\right\|_\lambda + \frac{|m|}{\lambda}\left\|\hbar\left(e_k(t)\right)\right\|_\lambda$$

$$\left\|y_{k+1}(t) - y_k(t)\right\|_\lambda \leq \frac{|m|}{\lambda - l_f}\left\|\hbar\left(e_k(t)\right)\right\|_\lambda \tag{9}$$

where $\lambda > l_f$.

From (8) and (9),

$$\begin{aligned}\left\|\hbar\left(e_{k+1}(t)\right)\right\|_\lambda &\le \frac{|\mu+m|}{\mu}\left\|\hbar\left(e_k(t)\right)\right\|_\lambda + \frac{l_f}{\mu}\cdot\frac{|m|}{\lambda-l_f}\left\|\hbar\left(e_k(t)\right)\right\|_\lambda \\ &= \left(\frac{|\mu+m|}{\mu}+\frac{l_f}{\mu}\cdot\frac{|m|}{\lambda-l_f}\right)\left\|\hbar\left(e_k(t)\right)\right\|_\lambda\end{aligned} \tag{10}$$

When the condition (7) is true, $\lim_{k\to+\infty}\left\|\hbar\left(e_k(t)\right)\right\|_\lambda = 0$. That $\hbar\left(e_k(t)\right)$ is a monotonically increasing odd function implies $\lim_{k\to+\infty}\left\|e_k(t)\right\|_\lambda = 0$, i.e. $\lim_{k\to+\infty}\left\|e_k(t)\right\| = 0$.

Theorem 2. Consider the following system

$$\dot{y}_k(t) = f\left(t, y_k(t)\right) + g\left(t, y_k(t-\tau)\right) + u_k(t) \tag{11}$$

where $y_k(t)\in R^n$ is the k-th iterative state vector, $f(t,y_k(t))$, $g(t,y_k(t-\tau))$ are the operator $[0,T]\times R^n\to R^n$, and satisfy

$$||f(t,y_{k+1}(t))-f(t,y_k(t))||\le l_f||y_{k+1}(t)-y_k(t)|| \tag{12}$$

$$||g(t,y_{k+1}(t-\tau))-g(t,y_k(t-\tau))||\le l_g||y_{k+1}(t-\tau)-y_k(t-\tau)|| \tag{13}$$

$u_k(t)$ is the k-th iterative control input, $\tau>0$ is time delay, and T is a constant. When $y_{k+1}(0)=y_k(0)$, the iterative learning controller is designed as (4). When $y_{k+1}(0)\ne y_k(0)$, the iterative learning controller is designed as (5). The Zhang gradient design formula can be used as (6). The other conditions are the same with Theorem 1. If there exist a constant $\lambda>0$ and a continuous function $\varphi(t)\ne 0$, $t\in[0,T]$, such that

$$\left(\frac{|\mu+m|}{\mu}+\frac{l_f}{\mu}\cdot\frac{e^{(l_f+l_g)t}|m|}{\lambda}+\frac{l_g}{\mu}\cdot\frac{e^{(l_f+l_g)(t-\tau)}|m|}{\lambda}\cdot\frac{\varphi(t-\tau)}{\varphi(t)}\right)<1 \tag{14}$$

then the system (10) can guarantee that $||y_d(t)-y_k(t)||$ is bounded and $y_k(t)$ can track $y_d(t)$ on $t\in[0,T]$, i.e. $\lim_{k\to+\infty} y_k(t) = y_d(t)$.

Proof. From $e_k(t)=y_d(t)-y_k(t)$, we know that $e_{k+1}(t)=e_k(t)+y_k(t)-y_{k+1}(t)$, so $\dot{e}_{k+1}(t)=\dot{e}_k(t)+\dot{y}_k(t)-\dot{y}_{k+1}(t)$, that is

$$\begin{aligned}-\mu\hbar\left(e_{k+1}(t)\right) &= -\mu\hbar\left(e_k(t)\right)+f\left(t,y_k(t)\right)+g\left(t,y_k(t-\tau)\right)+u_k(t) \\ &\quad -f\left(t,y_{k+1}(t)\right)-g\left(t,y_{k+1}(t-\tau)\right)-u_{k+1}(t) \\ &= -\mu\hbar\left(e_k(t)\right)-m\hbar\left(e_k(t)\right)+\left[f\left(t,y_k(t)\right)-f\left(t,y_{k+1}(t)\right)\right] \\ &\quad +\left[g\left(t,y_k(t-\tau)\right)-g\left(t,y_{k+1}(t-\tau)\right)\right] \\ &= -(\mu+m)\hbar\left(e_k(t)\right)+\left[f\left(t,y_k(t)\right)-f\left(t,y_{k+1}(t)\right)\right] \\ &\quad +\left[g\left(t,y_k(t-\tau)\right)-g\left(t,y_{k+1}(t-\tau)\right)\right]\end{aligned}$$

$$\begin{aligned}\hbar\left(e_{k+1}(t)\right) &= \frac{(\mu+m)}{\mu}\hbar\left(e_k(t)\right)+\frac{1}{\mu}\left[f\left(t,y_{k+1}(t)\right)-f\left(t,y_k(t)\right)\right] \\ &\quad +\frac{1}{\mu}\left[g\left(t,y_{k+1}(t-\tau)\right)-g\left(t,y_k(t-\tau)\right)\right]\end{aligned}$$

$$\begin{aligned}\left\|\hbar\left(e_{k+1}(t)\right)\right\| &\le \frac{|\mu+m|}{\mu}\left\|\hbar\left(e_k(t)\right)\right\|+\frac{l_f}{\mu}\left\|y_{k+1}(t)-y_k(t)\right\| \\ &\quad +\frac{l_g}{\mu}\left\|y_{k+1}(t-\tau)-y_k(t-\tau)\right\|\end{aligned}$$

Taking λ-norm, we have

$$\left\|\hbar\left(e_{k+1}(t)\right)\right\|_\lambda \le \frac{|\mu+m|}{\mu}\left\|\hbar\left(e_k(t)\right)\right\|_\lambda+\frac{l_f}{\mu}\left\|y_{k+1}(t)-y_k(t)\right\|_\lambda+\frac{l_g}{\mu}\left\|y_{k+1}(t-\tau)-y_k(t-\tau)\right\|_\lambda \tag{15}$$

$$
\begin{aligned}
y_{k+1}(t)-y_k(t) &= \int_0^t \left(\dot{y}_{k+1}(\tau)-\dot{y}_k(\tau)\right)d\tau + \left(y_k(0)-y_{k+1}(0)\right) \\
&= \int_0^t \left(\dot{y}_{k+1}(\tau)-\dot{y}_k(\tau)\right)d\tau \\
&= \int_0^t \left(f\left(t,y_{k+1}(\tau)\right)-f\left(t,y_k(\tau)\right)\right)d\tau + \int_0^t \left(u_{k+1}(\tau)-u_k(\tau)\right)d\tau \\
&\quad + \int_0^t \left(g\left(s,y_{k+1}(s-\tau)\right)-g\left(s,y_k(s-\tau)\right)\right)ds \\
&= \int_0^t \left(f\left(t,y_{k+1}(\tau)\right)-f\left(t,y_k(\tau)\right)\right)d\tau + \int_0^t m\hbar\left(e_k(\tau)\right)d\tau \\
&\quad + \int_0^t \left(g\left(s,y_{k+1}(s-\tau)\right)-g\left(s,y_k(s-\tau)\right)\right)ds
\end{aligned}
$$

$$
\begin{aligned}
\left\|y_{k+1}(t)-y_k(t)\right\| &\le \int_0^t \left\|f\left(s,y_{k+1}(s)\right)-f\left(s,y_k(s)\right)\right\|ds + \int_0^t |m|\left\|\hbar\left(e_k(s)\right)\right\|ds \\
&\quad + \int_0^t \left\|g\left(s,y_{k+1}(s-\tau)\right)-g\left(s,y_k(s-\tau)\right)\right\|ds \\
&\le l_f\int_0^t \left\|y_{k+1}(s)-y_k(s)\right\|ds + \int_0^t |m|\left\|\hbar\left(e_k(s)\right)\right\|ds \\
&\quad + l_g\int_0^t \left\|y_{k+1}(s-\tau)-y_k(s-\tau)\right\|ds
\end{aligned}
$$

Utilizing the retarded Gronwall-like inequality [15,33]and Lemma, we obtain

$$\left\|y_{k+1}(t)-y_k(t)\right\| \le e^{\left(l_f+l_g\right)t}\int_0^t |m|\left\|\hbar\left(e_k(s)\right)\right\|ds$$

$$\left\|y_{k+1}(t)-y_k(t)\right\|_\lambda \le \frac{e^{\left(l_f+l_g\right)t}|m|}{\lambda}\left\|\hbar\left(e_k(s)\right)\right\|_\lambda \tag{16}$$

$$\left\|y_{k+1}(t-\tau)-y_k(t-\tau)\right\|_\lambda \le \frac{e^{\left(l_f+l_g\right)(t-\tau)}|m|}{\lambda}\left\|\hbar\left(e_k(t-\tau)\right)\right\|_\lambda \tag{17}$$

From (15)-(17), we obtain

$$\left\|\hbar\left(e_{k+1}(t)\right)\right\|_\lambda \le \left(\frac{|\mu+m|}{\mu}+\frac{l_f}{\mu}\cdot\frac{e^{\left(l_f+l_g\right)t}|m|}{\lambda}\right)\left\|\hbar\left(e_k(t)\right)\right\|_\lambda + \left(\frac{l_g}{\mu}\cdot\frac{e^{\left(l_f+l_g\right)(t-\tau)}|m|}{\lambda}\right)\left\|\hbar\left(e_k(t-\tau)\right)\right\|_\lambda \tag{18}$$

It is easy to know that the solution of the equation $x_{k+1}(t)=\alpha x_k(t)+\beta x_k(t-\tau)$ is

$$x_k(t)=c\varphi(t)\left(\alpha+\beta\frac{\varphi(t-\tau)}{\varphi(t)}\right)^k \tag{19}$$

where α, β are given constants, c is an arbitrary constant, $\varphi(t)$ is an arbitrary function and satisfies that $\frac{\varphi(t-\tau)}{\varphi(t)}$ is a constant.

From (19) and the condition (14), $\lim_{k\to+\infty}\left\|\hbar\left(e_k(t)\right)\right\|_\lambda=0$. That $\hbar\left(e_k(t)\right)$ is a monotonically increasing odd function implies $\lim_{k\to+\infty}\left\|e_k(t)\right\|_\lambda=0$, i.e. $\lim_{k\to+\infty}\left\|e_k(t)\right\|=0$.

4 Example

For further illustration, we consider the following system

$$\dot{y}_k(t) = Ay_k(t) - Bf\left(y_k(t-\tau)\right) + u_k(t),$$
$$u_{k+1}(t) = u_k(t) + me_k(t) - \psi_{k,h}(t)\left(y_k(0) - y_{k+1}(0)\right)$$

where

$$A = \begin{pmatrix} 0.6\cos t & 0.02 \\ 0.1 & 0.8\sin t \end{pmatrix}, B = \begin{pmatrix} 0.5 & 0 \\ 0 & 0.5 \end{pmatrix}, y_k(t) = \begin{pmatrix} y_{1,k}(t) \\ y_{2,k}(t) \end{pmatrix},$$
$$f\left(y_k(t-\tau)\right) = \begin{pmatrix} \left|y_{1,k}(t-1)+1\right| - \left|y_{1,k}(t-1)-1\right| \\ \left|y_{2,k}(t-1)+1\right| - \left|y_{2,k}(t-1)-1\right| \end{pmatrix}$$

Taking m=–1.5, μ=2, l_f=1.43, l_g=2, $\varphi(t)$=$0.2e^{1.2t}$, $\psi_{k,h}(t) = \begin{cases} \pi\cos(\pi t), & t \in [0,1] \\ 0, & t \in (1,2] \end{cases}$. From the above example, it can be easily proved that the condition (13) of Theorem 2 is satisfied.

5 Conclusion

In this paper, considering the iterative learning control problem for nonlinear systems without and with time delays, and combining with Zhang-gradient method, the novel controllers, which can guarantee the robust convergence of the tracking error, are designed.

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